A Prison Population Projection Methodology Using National Corrections Reporting Program Data

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This paper discusses a methodology that uses National Corrections Reporting Program (NCRP) data to predict the size of a state's prison population for some specified year in the future. It uses Arizona as an example and makes a five-year projection. Although Arizona is a concrete example, this is a methodology paper. Expectations are that the methodology can be improved with additional work.

To build projections, the methodology uses three observed data sources and two unobserved (and hence estimated) data sources. The observed data are the admission flow of offenders into prisons between 2011 and 2015 (which comprises January 1, 2011 through December 31, 2015), the stock of offenders as of 2010 (specifically December 31, 2010) and the stock of offenders as of 2015 (specifically December 31, 2015).[1] The unobserved data are the future flow of offenders between 2016 and 2020 inclusive and the probability that members of the 2015 stock and 2016-2020 flow will remain incarcerated as of 2020.

This paper first explains the methodology. It then demonstrates the method's applicability using Arizona NCRP data. A third section raises some methodological considerations. The methodology applies to most states reporting to the NCRP and the conclusion briefly describes modifications suitable for other states.

Methodology

This paper introduces a mixed stock/flow-based method for projecting future prison stocks. The stock-based component projects the members of the 2015 prison stock who will remain in prison at the end of 2020. The projection is based on the size and composition of the 2015 stock, the transition probabilities for offenders in the 2010 stock remaining in the 2015 stock, and a steady-state assumption that conditional transition probabilities for the 2010 stock apply to the 2015 stock. The flow-based component projects the members of the 2016-2020 admission flow who will remain in prison at the end of 2020. The flow-based component is based on estimates from the 2016-2020 admissions flow, the conditional transition probabilities for offenders in the 2011-2015 admission flow who appear in the 2015 stock, and a steady-state assumption that conditional transition probabilities for the 2011-2015 admission flow remain the same for the 2016-2020 admission flow. The stock-based and flow-based projections are then combined.

Data come from the NCRP, a Bureau of Justice Statistics program that annually updates daily admission flows into and daily release flows from state prisons.[2] NCRP term records enable easily-constructed prison stocks from flows.[3] As discussed later in this paper, at a minimum a state that wants to project stocks Y years into the future must have at least Y years of prison term data in the NCRP. (See the

[1] For some purposes, calculations use NCRP data that predate 2010. But a conceptual simplification is to focus on 2010 and later. When other data are used, this paper will clarify.

[2] A term record comprises the start and end date of an offender's prison term. The end date is open for offenders in prison at the end of a reporting period. Term records include all stays in prison that overlap any part of an *observation window*. The observation window begins in 2000 for many states, currently extends through 2015, and is updated yearly. While all states report to the NCRP, term records cannot be built for all states. Thus, the projection methodology discussed in this paper applies to most but not all states.

[3] See the previous note. The NCRP comprises term records that were active any time during an observation window. To construct the stock for any date, a user selects all term records with admission dates on or before the stock date and release dates after the stock date.

previous two notes for a definition of prison term.) For example, if a state seeks to project 2020 stocks, it must at a minimum have 2011-2015 prison term data. Further, projections improve when a state can provide Y+δ years of term data. This paper assumes δ = 7, but smaller δ values might be used.

The Stock-Based Component

For the stock-based component, let:

S_{Yk} This is the stock of offenders convicted of offense type k who are in prison at the end of year Y. A stock population is always a year-end population.[4] For now, this paper leaves the definition of offense type vague and clarifies later.

$S_{Y,Y+5k}$ This is the stock of offenders convicted of offense type k who were in prison at the end of year Y and who remain in prison at the end of year Y+5.

P_{Yk} This is the proportion of the stock at the end of year Y who remain in prison at the end of year Y+5.

This paper always assumes a five-year projection, but the method accommodates projections of different lengths.

For offense type k the estimated transition probability P_{2015k} is:

$$[1] \qquad \hat{P}_{2015k} = \frac{S_{2010k,2015k}}{S_{2010k}}$$

With this estimate, the projected size of the 2020 prison population that comes from the 2015 stock is:

$$[2] \qquad STOCK_{2020,\,from\,stock} = \sum_{k=1}^{K} \hat{P}_{2015k} S_{2015k}$$

In formula [2], $STOCK_{2020,\,from\,stock}$ is the number of offenders who were in the 2015 prison stock and remained in the 2020 prison stock. They were not released between 2015 and 2020. S_{2015k} is the number of offenders associated with offense type k who were in the 2015 prison stock. $\hat{P}_{2015k}$ is the estimated proportion of offenders associated with offense type k who were in the 2015 stock and remained in prison through 2020.

An important assumption is that $\hat{P}_{Yk}$ is time invariant over the five-year period from 2010 to 2015. This is close to assuming that the distribution of time spent in prison, conditional on offense-type k, has not changed from 2015 to 2020. As explained subsequently, defining k narrowly and conditioning estimates on covariates increase the plausibility of this steady-state assumption.

[4] The NCRP is calendar-based. A state may prefer a fiscal-year projection. This would require a minor programming change. For example, if the state required a projection for the beginning of October rather than the end of December, the projection period would be 57 months rather than 60 months.

The Flow-Based Component

The flow-based component accounts for offenders who will enter prison between 2016 and 2020 inclusive and who will remain in prison as of the end of 2020. Some notation will be helpful:

T This is the date that an admission flow begins. It is always January 1 of year T.

$T+4$ This is the date that an admission flow ends. It is always December 31 of year T+4. For example, an admission flow might occur between January 1, 2016 and December 31, 2020. Interest is focused on how many members of that admission flow are in prison at the end of $T+4$.

t This is the date when an offender enters prison. It is only relevant between T and $T+4$.

The probability that an offender, admitted to prison on date t, remains in prison as of date T+4 is:

$$Q_k(T+4-t) \tag{3}$$

The k subscript indicates that this function is specific to offense type. This function is estimated for all offenders admitted between 2011 and 2015. That is, set T=January 1, 2011 and estimate the function using data for admissions between January 1, 2011 and December 31, 2015. An important assumption is that $Q_k(2015-t)$ is time-invariant, so the function estimated using 2011 through 2015 admissions is applicable to 2016 through 2020 admissions. As before, this is close to assuming that the distribution of time-served, conditional on offense type-k, will be the same between 2016/2020 as it was between 2011/2015. Concern for this steady-state assumption argues for basing estimation on the most recent admission cohorts. As discussed subsequently, using stratification increases the plausibility of this assumption.

The methodology also requires an estimate of the flow of admissions between 2016 and 2020. Estimating this flow requires using statistical techniques that are described below. For now, define:

$\hat{A}_{tk}$ This is the estimated number of admissions at time t for offense type k.

Then the estimate of the number of offenders admitted between 2016 and 2020 who remain in prison as of the end of 2020 is:

$$STOCK_{2020,\,from\ flow} = \sum_{k=1}^{K} \sum_{t=2016}^{2020} Q_k(T+4-t)\hat{A}_{tk} \tag{4}$$

The projected stock for 2020 is:

$$STOCK_{2020} = STOCK_{2020,\,from stock} + STOCK_{2020,\,from\ flow} \tag{5}$$

In addition to projecting the overall AZ 2020 stock population, this paper will illustrate that nothing prevents the stock estimates from being reported by offense type or clusters of offense types. For some purposes this disaggregation is useful.

Statistical Analysis

Equations [1] and [3] and A_{tk} are estimated using regressions applied to stratified samples. Stratification for the Arizona projection comes from interacting two variables: offense seriousness and observable criminal record. This list of stratification variables could be expanded.

- The first variable used for stratification is offense seriousness. This paper recognizes seven offense seriousness categories that range from the least serious offenses to the most serious offenses and an eighth category for drug offenses[5]. Seriousness is determined by median time served in prison based on the offense of conviction.[6] The offense of conviction is a reclassification of BJS_OFFENSE_1 in the NCRP data where attempts, conspiracies, and completed offenses have been treated as part of the same offense type. The categories are constructed so that approximately 20 percent of non-drug offense admissions fall into each of the first three categories, approximately 10 percent of non-drug offense admissions fall into each of the last four categories, and the first seven categories increase by offense seriousness.[7]
- The second variable used for stratification is observable criminal record, as defined by prior incarceration in state prison. A prior record variable is coded 0 to 7. A zero denotes that the offender had not been released from prison within 7 years of his or her admission for the current offense. A one denotes that the offender was admitted to prison within one year of a previous release, a two denotes that he or she was admitted within one to two years of the current admission, and so on. For stratification, this variable is collapsed into 0, 1, 2 and 3 (where 3 includes 3 through 7).[8]

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[5] In several states, the reporting of drug offenses is inconsistent over time. Drug amounts differentiating possession from sale may change or many drugs can be captured by a single offense code. To limit the impact of changes in the reporting of drug offenses, they have been separated into their own offense seriousness category.

[6] Median time in prison is estimated using cohorts released from prison between 2000 and 2015. The median is conditioned on offense type, generally considered to be the most serious offense when an offender is convicted of multiple different offenses. Once the median is established, everyone admitted to prison for a particular offense type is assigned that median. Then the data are sorted by the assigned medians and offenders are placed into bins so that the first bin contains the least serious offenses and subsequent bins contain progressively more serious offenses. The first three bins are each intended to contain 20% of the admissions and the next four bins are each intended to contain 10% of admissions each (excluding drug offenses). In fact, these percentages are not achieved because the distribution of median time-served is discrete (not continuous) and the same offense types are never split across bins.

[7] Much of the analysis is based on admissions, so the data are stratified such that each offense seriousness category has a large number of admissions. Nevertheless, offenders convicted of the more serious offense tend to spend more time in prison, so they are more important for the stock; that is why the most serious offense categories are more narrowly defined as offense codes comprising 10% of the flow rather than offense codes comprising 20% of the flow.

[8] Seven years prior to admission is not observable for all admissions to prison or in all states. For example, in a state where data is first collected in 2000, we are only able to observe the four years preceding admission for an offender admitted to prison in 2004. As a result, our classification of offenders is less accurate toward the beginning of our observation window. To account for this, our prior criminal history variable is recalibrated if we cannot observe at least seven years prior to admission in 2010 (five years before the end of the observation window). For example, if we only have data back to 2006, then the longest complete window we can observe for

These stratification variables are used for illustration. It seems highly likely that offense seriousness should be a stratification variable because offense seriousness is a good predictor of time-served and in many states offense seriousness can be subject to actual crime patterns or public policy regarding the handling of crimes by seriousness. It seems highly likely that criminal history should be a stratification variable given renewed interest in post-confinement supervision revocations and recidivism.[9]

The combination of 8 offense seriousness levels and 4 criminal history categories results in 32 strata. Estimation applies the mixed stock/flow methodology to each of the stratum and then sums results across strata. Note that these strata determine k, the offense type used in the original equations, clarifying the earlier definitional ambiguity.

These choices for stratification may seem novel. Methods are sensitive to steady-state assumptions and many jurisdictions are modifying sentencing and correctional practices to shift prison use from less serious to more serious offenses and to shift prison use from first-time to repeat offenders. Stratification on offense seriousness and criminal record increases the plausibility that the steady-state assumption holds. Consider that a category such as "violent offense" is likely to be a mix of more or less serious offenses (homicide and simple assault, for example). If the size of the components of this mixture is changing, the steady-state assumption cannot hold. When offenses are combined based on seriousness, the components may also change, but since the components are alike regarding time-served, any change will be less important for projections. Consider also that if sentencing and correctional reforms are focused on an offender's criminal history, then trends based on prior record are likely to be more accurate than are trends that mix first-time and repeat offenders together.

Obviously, using other variables to represent criminal record and to identify citizenship may be better, but those preferred variables are not part of the NCRP. (For example, a risk score might be a substitute for recency of a prior prison term.) Given the goal of prediction, however, even incomplete stratification is preferable to no stratification.

In addition to stratification, the regressions use independent variables. Their use varies from regression-to-regression, depending on the regression's purpose, but a complete list of independent variables is:

Off This is a set of dummy variables denoting that the offender was convicted of (reclassification of BJS_Offense_1 in the NCRP data). The BJS_Offense code is at the level of homicide, armed robbery and so on, so it is finer grained than the offense seriousness level used for stratification. That is, multiple BJS_Offense codes fall within each of the 8 offense severity categories.

Prior This is a set of dummy prior record variables coded 0 to 7. When used as covariates, Prior always enters the analysis as a set of dummy variables. Note, however, Prior does not vary

an offender admitted in 2010 is 4 years. In such a state, we would treat observed releases 5-7 years prior as 0s to maintain consistency for our entire estimation window.

[9] If offense seriousness and criminal record are adopted as stratification variables, a researcher performing projections might search for other stratification variables. To be useful, within each of the offense seriousness criminal record categories, a research might search for variables that (1) change over time and (2) affect time-served. "Over time" probably means between 2010 and 2015 since this period best informs about changes between 2015 and 2020.

within the prior record strata 0, 1 and 2 so there is no reason to enter the prior dummy variables into the regressions for these strata.

Date This is the offender's admission date coded as days for regressions used to estimate [1] and [3] and coded as months to estimate future admissions.

TServ This is time-served in prison for offenders in the stock; it is not used directly in any regression.

TSent This is time-sentenced to prison for offenders in the stock; it is not used directly in any regression.

Ratio This is TServ/TSent or the proportion of the term already served. Ratio appears in some regressions; its component parts do not.

To estimate equation [1], the analysis identifies every offender who was incarcerated at the end of 2010. In preparation for using a regression, the analysis assigns each of these offenders a dummy dependent variable coded 1 if the offender was in the 2015 stock and coded 0 otherwise. Independent variables are Off, Prior, and Ratio. Estimation uses an OLS regression. Predictions from this regression become a version of P_{Yk} that depends on all covariates. Because of the stratification, some covariates are collinear. For example, when stratification is on a criminal record of 0, Prior necessarily equals 0. Because interest is with prediction, collinearity is immaterial (McCulloch and Searle 2001).

To estimate equation [3], the analysis identifies every offender who was admitted to prison between January 1, 2011 and December 31, 2015. In preparation for the regressions, each offender is assigned a dummy variable coded 1 if the offender was in the 2015 stock and coded 0 otherwise. Independent variables include Date (which represents T+4-t in the equation), recorded in months. A separate regression is estimated for each of the five years of predicted admissions and predicted probabilities are combined for form a single equation[10]. No other variables need enter the regression for reasons explained below. Estimation uses a logistic regression.

The remaining estimation problem is to project the flow of admissions between 2016 and 2020. For this purpose, estimation uses a vector autoregression statistical model. As before:

A_{tk} This is the number of admissions for offense type k during month t.

By extension:

[10] Our flow based predictions are based on the proportion of offenders admitted 1-60 months prior to December 31, 2015 still being incarcerated on December 31, 2015. The predicted proportion of offenders still incarcerated on December 31, 2015 who were admitted in the year prior is different when the model is based on 12 months of admissions compared to 60 months of prediction. Since we are interested in making 1-4 year population projections in addition to the five year estimates, we need the prediction proportions to be stable regardless of the number of predicted years. We determined that this was best achieved by predicting the 1 year monthly proportions (admissions 1-12 months before the end stock) separately from the other data. The other four years are also predicted independently (one prediction for the admissions 13-24 months before the end of the observation window, another one for the admissions 25-36 months, etc.). To make the full flow-base prediction, the computed proportions are stitched together into a single equation.

R_{tk} This is the number of releases for offense type k during month t. Although releases did not enter into the earlier modeling, monthly releases are useful for predicting monthly admissions, a central variable in the model.

Then the regression model is:

[6] $$A_{tk} = \sum_{j=-1}^{-J} A_{jk}\alpha_{kj} + \sum_{j=-1}^{-J} R_{jk}\beta_{kj} + trend_k + e_{tk}$$

J represents the number of lags used in the analysis. The variable trend is a linear time-trend that is required because the time-series is not stationary. The error term is assumed homoscedastic and independent although for prediction purposes, these assumptions are not essential. Prediction of the future flow is done by recursion. For example, to predict admissions for January 2016, the methodology uses past realizations of admissions and releases through December 2015. To predict admissions for February 2016, the methodology uses past realizations plus predictions of admissions and releases for January 2016. This recursion continues until the predictions reach December 2020. Stata routines var and fcast perform the calculations.

The vector autoregression model is applied to each of the strata in batch mode. Predictions may increase or decrease beyond a reasonable range, so a side-constraint is placed on the projections. The 2016-2020 projections can never be less than lower-limit parameter times the average number of admissions for 2011 through 2015. The 2016-2020 projections can never be more than higher-limit parameter times the average number of admissions for 2011 through 2015. For this paper, the lower-limit parameter equals 0.5 and higher-limit parameter equals 1.5, but sensitivity testing suggests that changing the limits to 0 and 2 have little effect (about 100 offenders) on projections.

As shorthand for equation [3], define:

Q_{tk} This is the proportion of offenders of offense type k admitted during month t who remain in prison as of the end of December 2020. This estimate is a simple monthly aggregate of the regression used to estimate [3].

Then the 2020 stock resulting from the 2016-2020 flow is:

[7] $$STOCK_{2020,\,from\ flow} = \sum_{k=1}^{K} \sum_{j=Jan2016}^{Dec2020} A_{tk} Q_{tk}$$

Because of this final formula, there is no reason to add additional covariates to the logistic regression used to estimate equation [3].[11] Recall, however, that these regressions are run separately on multiple partitions of data, so implicitly covariates enter the analysis as fully interacted variables. Predictions of future admissions come from the regression results.

[11] If there were additional covariates in the model, the predictions would still be aggregated across covariate values when applied to [5].

As represented by equation [6], the regression has a simple formulation, but this is deceptive. An analyst must make two choices: (1) What window of data should be used in the estimation? A "window" refers to years of NCRP data.[12] The answer might be "all the NCRP" data, but this is unlikely to be correct because old admission data are unlikely to be informative about current admission practices. (2) How many lags should be used in the analysis? The answer might be "a very large number of lags" but again this is not likely to be optimal because admissions during distant periods are unlikely to be useful predictors. Identification of data windows and lags comes from formal diagnostics developed using Stata software. The diagnostics will be described in a subsequent version of this paper.

The model imposes a linear trend.[13] In fact, over long periods, admissions into state systems may not be linear and the model will be misspecified. However, the diagnostic procedures mentioned above will seek to limit the data window to recent periods when trends are linear or at least monotonically increasing or decreasing. It is possible that no such period of monotonicity of trends exists for a state. There is no substitute for examining the trends and results from the vector autoregression to assure that results look reasonable.

Note the role of stratification variables and covariates. First, if Arizona were truly in a steady-state, the use of these variables would be unnecessary. But the correctional system may be changing with regard to admissions by offense seriousness and other stratification variables. For example, over time offenders convicted of the least serious offenses may be treated more leniently and less frequently enter prison, while those convicted of the most serious offenses may be treated relatively more harshly. Then, across all offense types, a steady-state would not hold, but within an offense seriousness category, a steady-state is more likely to hold and departures from the steady-state are likely minor. Hence stratification and controls for covariates are expected to improve predictions by increasing the plausibility of steady-state assumptions.

The fact that a variable helps explain does not mean that that variable materially improves predictions. Men may be treated differently than women, yet if the mix of men and women do not change much given stratification on other variables and the covariates used in the analysis, introducing sex as a stratification variable or covariates will not reduce bias. The purpose of stratification and the use of covariates is to account for departures from the steady-state that are correlated with stratification variables and covariates.

In summary, for each stratum:

- The methodology estimates the number of offenders in the 2015 prison stock who will appear in the 2020 prison stock. The estimate is based on the size and composition of the 2015 prison

[12] There is some ambiguity with this definition. A "window" defines time period over which the dependent variables admissions and releases are observed. Suppose that this is M months. However, if there are L lags, then the required data must span M+L months.

[13] An analyst might assume a non-linear trend and substitute a polynomial for the linear time-trend. The authors of this report consider this bad practice. When carried from the domain of support (that is, from the months with observed data) to the domain of prediction (that is, five years into the future), a polynomial that "fits" the data well may be very misleading about the future. The authors' opinions are that if a linear trend is not persuasive, then neither are projections, and there is probably no good correction.

stock and observations of whether similar offenders in the 2010 prison stock appeared in the 2015 prison stock.

- The methodology estimates the number of admissions between 2016 and 2020. The estimate is based on trends observed prior to 2016.
- The methodology estimates the number of offenders who appear in the 2016 through 2020 flow who will appear in the 2020 prison stock. The estimate depends on the pre-2015 release rate for offenders who appeared in the flow between 2011 and 2015.

Final estimates are the sum of the stock-based component and the flow-based component summed across strata.

Comments on Predicting Future Admission Flows

Calculations depend partly on steady-state assumptions regarding the distribution of time-served in prison conditional on the offense stratification. There is no way to be sure of the steady-state assumptions, although in the absence of contrary external information – such as changes in sentencing guidelines or release practices – the steady-state assumption might be seen as justified.

Predicting future flows is more uncertain. If admission flows grew linearly, even with variation about the linear trend, prediction would be fairly straightforward. An analyst might estimate a linear regression with admissions as the dependent variable and time as an independent variable. The regressions would be conditional on the stratum.

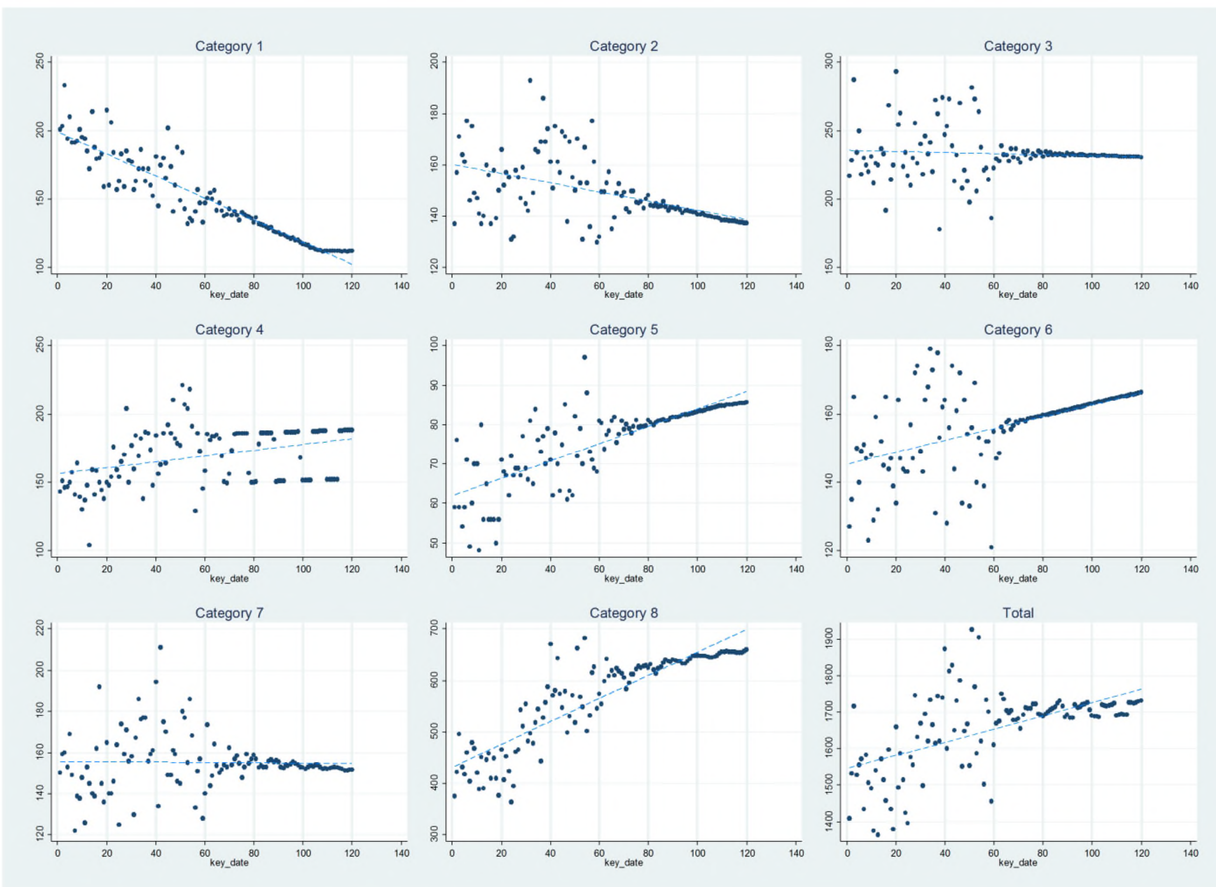
However, the stream of admissions is not so well-behaved. Between 2000 and 2015, it is not unusual to see admissions increase, reach a peak and then decrease. Other patterns sometime occur. This suggests that whatever trends occur during the year or few years before 2015, there is no assurance that those trends will continue. Projecting trends five years into the future has both statistical and non-statistical uncertainty.

The approach taken into this paper is to use a technique called vector autoregression to project future admissions. It is likely that some unobserved variables and likely several unobserved variables affect the admission flow. For example, more arrests for burglary probably will result in more admissions for burglary, and more lenient sentences for drug possession likely will result in fewer admissions for drug possession. In the absence of observing these causal factor and without knowledge of the delay between when they happen and when admissions appear, statisticians will sometimes use lagged values of what is observed – admissions. Intuitively this makes sense: Recent trends in admissions would seem to be good predictors of future admissions in a world where changes are not too radical. In addition, prison admissions are partly driven by an observable – prison releases. This is because a proportion of offenders are readmitted to prison for violating the conditions that govern their post-confinement community supervision. Therefore, lagged values of releases help predict future admissions. The analysis used for this paper predicts admissions at time t using lagged values of earlier admissions and releases plus a linear trend.

Returning to equation [6], a fundamental difficulty is to determine (1) how many years of data should be used to estimate the parameters associated with the lagged variables and (2) how many lags should enter the model? An appendix (in a later version of the paper) describes diagnostics used to answer these two questions. The figure below shows a version of projections used for this paper. Rather than shows the projections for every stratum, figure 1 shows projections for the eight offense seriousness categories and for all categories combined.

The horizontal axis is months. For the first 60 months, the graph reports observations of admissions; for the next 60 months, the graph reports projections. To assist with interpretation, the dotted line is a linear fit of the observations and predictions. As an illustration, look at offense category 1, which appears in the upper left panel. During the last 60 months of the observation period, there was a general downward trend in category 1 admissions. During the 60 months of the prediction period (months 61-120), the trend is projected to continue. As another illustration, look at offense category 4. During the observation period, the trend was upward, and the analyses projects that the trend will continue, although at a somewhat diminished pace. The bottom right panel suggests that overall admissions, which grew slightly over the observation period, will remain fairly constant over the projection period.

Figure 1 -- Admissions (months 1-60) and Projected Admissions (months 61-120) by Offense Seriousness Category



Results

Table 1 shows primary results. The offense seriousness category represents the eight offense seriousness categories where category 1 is the least serious, category 7 is the most serious, and category

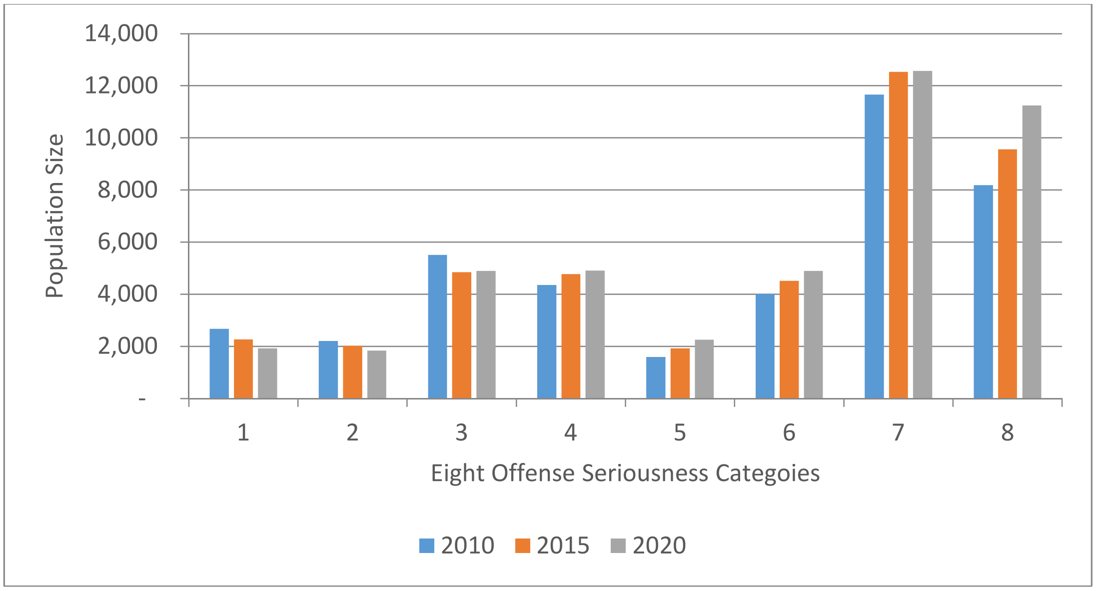
8 is comprised of drug offenses. The column “2010 Stock” reports the stock of offenders in Arizona prisons as of the end of 2010. The column “2015 Stock” reports the stock as of the end of 2015. Under the 2020 Projections, the first column is the estimated 2020 prison stock that comes from the 2015 stock. As would be expected, this is a fairly small number for the least serious offenses, for which offenders serve the shortest terms, and it a larger number for the more serious offenses, for which offenders serve the longest terms. The second column under the 2020 Projections is the estimated 2020 prison stock that comes from the 2016-2020 flow. The respective numbers in these last two columns emphasize the importance of the projected admission flow for five-year projections. Overall, the 2020 Arizona prison stock is projected to be 443522. This is up from 42,433 in 2015 and continues a climb from 40,173 to 42,433 between 2010 and 2015.

Table 1 -- Projections for the 2020 Arizona Prison Stock

				Projections for 2020		
Offense Seriousness Category		2010 Stock	2015 Stock	From 2015 Stock	From 2016-2020 Flow	Total
seriousness -->	1	2,669	2,261	114	1,803	1,917
	2	2,201	2,022	319	1,518	1,837
	3	5,513	4,841	454	4,447	4,900
	4	4,357	4,774	961	3,943	4,904
	5	1,588	1,928	228	2,021	2,249
	6	4,006	4,511	691	4,208	4,899
	7	11,657	12,532	6,489	6,085	12,574
	8	8,182	9,564	812	10,428	11,240
	All	40,173	42,433	10,067	34,455	44,522

Figure 2 summarizes aspects of the growth over a ten-year period. The figure shows that the two least serious offense categories, each of which accounts for roughly twenty percent of the non-drug related admissions, comprise a relatively small proportion of the Arizona prison stock. Moreover, their share of the prison stock has been declining over time. The bulk of prison use can be attributed to offenders convicted of the most serious offenses as well as the drug offenders. The figure shows that the four most serious offense categories, each of which accounts for roughly ten percent of the non-drug related admissions, comprise a comparatively large proportion of the Arizona prison stock. Moreover, the share of the prison stock associated with the most serious offense categories has been growing. The largest growth from 2010 to 2020 is associated with changes in the number of drug offenders in the year end stock. Projections suggest that Arizona prison stock will increase and its composition will change to include a larger proportion of the most serious offense categories and drug offenders.

Figure 2 -- A summary of Prison Population Growth from 2010 through 2020 (2020 Projected)



Some of the bars look peculiar. One might expect the bars associated with category 5 to be larger than the bars associated with category 4 given that each of these categories captures roughly ten percent of admissions and offenders in category 5 serve longer on average than offenders in category 4. The explanation is that the offense codes are not evenly distributed in the population, leading to lumpy categories. Category 5 is actually much smaller than 10 percent of admissions.[14]

The next four-part table replicates the structure of table 1 but distinguishes the criminal history categories. Offenders who have not previously served prison time are the largest category. Their share of prison usage decreased from 2010 to 2015 and is projected to decrease slightly. In contrast the number of offenders in the other criminal history categories are projected to increase.

[14] As a stylized illustration, suppose there were only two offense seriousness categories and two offense categories. Suppose furthermore than the first offense category accounted for 75% of admissions. Then it is impossible to create equal-sized offense seriousness categories because the offense codes never span offense seriousness categories.

Table 2 -- Projections for the 2020 Arizona Prison Stock (Stratified by Criminal Record)

No Previous Prison Stays

				Projections for 2020		
	Offense Seriousness Category	2010 Stock	2015 Stock	From 2015 Stock	From 2016-2020 Flow	Total
seriousness -->	1	1,184	891	25	523	548
	2	1,237	1,014	171	703	874
	3	2,573	1,957	150	1,720	1,870
	4	2,769	2,713	509	1,988	2,497
	5	733	797	121	727	847
	6	1,887	1,959	268	1,729	1,997
	7	9,554	9,579	5,167	3,986	9,154
	8	4,894	5,098	348	5,115	5,463
	All	24,831	24,008	6,759	16,492	23,251

Released within 1 Year of the Current Admission

				Projections for 2020		
	Offense Seriousness Category	2010 Stock	2015 Stock	From 2015 Stock	From 2016-2020 Flow	Total
seriousness -->	1	323	239	8	130	138
	2	318	365	39	280	318
	3	909	764	63	598	661
	4	425	499	83	475	558
	5	249	250	16	273	289
	6	698	632	61	571	632
	7	575	711	262	507	769
	8	931	1,191	65	1,453	1,518
	All	4,428	4,651	597	4,287	4,884

Released within 1-2 Years of the Current Admission

				Projections for 2020		
	Offense Seriousness Category	2010 Stock	2015 Stock	From 2015 Stock	From 2016-2020 Flow	Total
seriousness -->	1	385	268	21	163	185
	2	272	238	52	112	164
	3	926	804	99	648	747
	4	503	567	134	449	584
	5	254	325	38	311	350

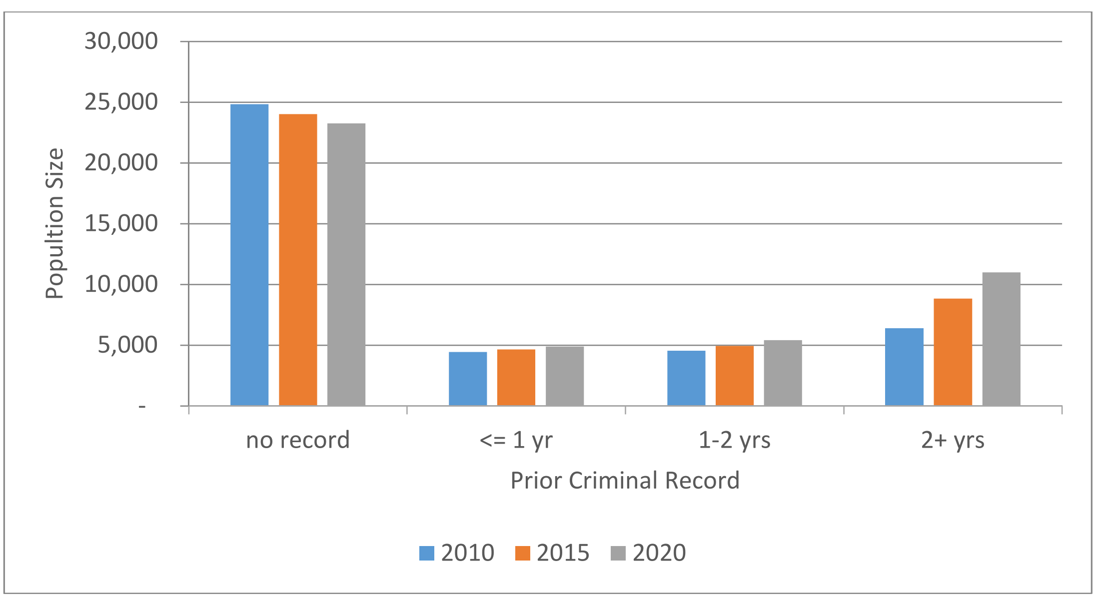
6	661	812	166	802	968
7	640	880	440	551	991
8	896	1,055	127	1,290	1,417
All	4,537	4,949	1,078	4,327	5,405

Released within 2-7 Years of the Current Admission

				Projections for 2020		
	Offense Seriousness Category	2010 Stock	2015 Stock	From 2015 Stock	From 2016-2020 Flow	Total
seriousness -->	1	777	863	60	987	1,046
	2	374	405	57	424	481
	3	1,105	1,316	141	1,481	1,622
	4	660	995	235	1,031	1,266
	5	352	556	53	710	762
	6	760	1,108	196	1,106	1,302
	7	888	1,362	619	1,040	1,660
	8	1,461	2,220	271	2,570	2,842
	All	6,377	8,825	1,633	9,349	10,982

Figure 3 summarizes results from table 2. It shows that repeat offenders are projected to be a growing proportion of the Arizona prison stock. First-time offenders (e.g. those who lack earlier prison stays as far as the NCRP reveals) are projected to be a declining proportion of the Arizona prison stock.

Figure 3 -- Observed 2010 and 2015 Prison Stock and Projected 2020 Prison Stock by Criminal Record



Comments

This is a methodology paper. Expectations are that the methodology can be improved with additional work. The following sections consider some possible improvements.

Further Stratification

The basic model uses offense seriousness and criminal history as stratification variables. As shown above, it is straightforward to build tabulations within stratification variables (e.g. by criminal history category) as well as across stratification variables (e.g. all strata combined). But an analyst may want to build projections for a group not identified by the stratification variables and this is possible.

As an illustration, about 1 of 10 prisoners are women, and women could be an additional stratification variable. Although the program is not designed to recognize sex as an additional stratification variable, a user can select the data so that only women run through the data manipulations. Essentially this is the same as stratification, but results for men and women are not then combined. The program just reports results for women.[15]

A problem is that when the data are cut by this additional stratification variable, partitions may be empty or have few observations.[16] Empty strata are not problematic because if the past showed zero observations for a given stratum, presumably the best estimate for the future is also zero. Having few observations per stratum is a larger problem because statistical analysis is tenuous in the absence of adequate sample size.

When sample sizes are small, it is possible for P (from equation [1] or equation [3]) above to be zero (no 2010 inmates remain in prison as of 2015) or one (all 2010 inmates remain in prison as of 2015). Stata will not estimate a regression when the dependent variable has no variance, but it is straightforward to avoid the regression problem and set P to 0 or 1 as warranted.

The vector autoregression estimation requires at least some data. When there are fewer than 10 past admissions or 10 past releases, the program simply sets future admissions to 0. This will bias estimates downward, but the effect is probably small given that this adjustment only happens when there are few past observations, which implies few future admissions. An alternative approach would be to create fewer offense seriousness levels.

Table 4 is a demonstration of applying the prison projection methodology to a new stratum: women. The table has the same form as the previous tables but the sample size is only about one-tenth the size used in the earlier tables. Comparing tables 1 and 4 suggests that women are a declining proportion of the Arizona prison stock, but the change is small and likely within the margin of sampling and non-

[15] When the sample is limited to women, the vector autoregression analysis should be repeated. Because this paper is for illustration, the analysis does not take that step. Instead, it assumes that the window and lag structure for men and women combined is the same as the window and lag structure for women alone. In fact, this may be an acceptable assumption because vector autoregression for the sparse data structure provided for women may have high sampling variance.

[16] The offense seriousness category is based on the complete sample. The distribution of admissions by offense category for woman alone is different from the distribution of admissions for men and women combined. This fact can cause one or more stratum have small numbers of observations.

sampling error. It would not be unjustified to conclude that women will remain slightly less than 10% of the Arizona prison stock.

Table 4 -- Projections for the 2020 prison Stock (Women)

	Offense Seriousness Category	2010 Stock	2015 Stock	Projections for 2020: From 2015 Stock	Projections for 2020: From 2016-2020 Flow	Projections for 2020: Total
seriousness -->	1	242	225	2	194	196
	2	225	248	28	237	265
	3	957	839	48	874	922
	4	274	356	31	345	376
	5	44	53	1	34	35
	6	296	346	31	391	421
	7	543	597	272	237	509
	8	1,146	1,335	61	1,390	1,451
	All	3,727	3,999	473	3,702	4,176

Projecting Future Admissions

The vector autoregression takes into account lagged admissions and lagged releases. The question is whether the predictions would be improved by adding additional explanatory variables. For example, one might postulate a causal sequence:

Demographics → offenses → arrests → convictions → sentences → admissions

Any variables prior to admissions in this causal sequence might be used to predict, but at least two considerations come into play. The first is that these variables can be difficult to measure in a timely fashion, and any variables used in the statistical model must be projected into the future. For example, arrests are reported by the FBI, but not with the specificity used for the prison projection model, and typically with a delay measured in years. The second consideration is that econometricians have reported that vector autoregression often leads to better predictions than do more complex causal models (Greene, 2008, p. 694), so when prediction alone is the objective, simple vector autoregression may be recommended.

Nevertheless, developing better models of future admissions may be a productive area of investigation for improving the projections of future prison stocks. Especially troubling is the situation where a state has recently undergone policy changes that will affect projections of future admission flows. As described in the section immediately below, the program allows its user to override projections to account for external information, but the override is crude. An alternative is to build a more complex projection model for future admissions, but applying that alternative goes beyond the scope of this paper.

External Information

The accuracy of projections depends upon the adequacy of steady-state assumptions. The method proposed in this paper mixes two forms of projection: a stock-based component and a flow-based component. For the stock-based component, the 2015 stock is known, and the projection of the 2020 stock derived from the 2015 stock depends on estimates of which members of the 2015 stock will remain in prison through 2020. In turn, that latter estimate presumes that the turnover in prison stock between 2020 and 2015 is the same as the turnover in prison stock between 2015 and 2000. With stratification and the use of covariates, a steady-state assumption seems justified, but external information should factor into the projections. For example, if the state adopts a new early release policy, then surely that new policy should be factored into projections. For the flow-based component, neither the 2016-2020 flow nor the probability that members of that flow will remain in prison through 2020 are known. Projections presume that trends in admissions prior to 2015 predict the flow post-2015 and that time-served for those new prison arrivals will remain about the same as it was for pre-2015 arrivals. Stratification increases the plausibility of those assumptions, but if the state alters its admission or time-served practices, surely those changes should be factored into the projections.[17] The methodology employs a simple approach to introducing adjustments based on external information.

First, within each stratum, the program predicts the number of offenders in the 2020 prison stock from the 2015 prison stock. Suppose that external information suggests that this number is likely to be smaller – for example, because the state is expected to adopt an early release program for some offenders defined by the strata. If judgement is that the stock will fall by 15%, the program's prediction might be multiplied by 0.85. Second, within each stratum, the program predicts the number of offenders in the 2020 prison stock from the 2016-2020 admission flow. Suppose that external information suggests that the number is likely to be 25% larger – for example, because the state is expected to crack down on certain types of offenders. The program's predictions might be multiplied by 1.25. The program will apply these multipliers if required. See the subsection immediately below on program operations.

Correctional reforms are not geared to the offense seriousness categories used in this report. Suppose that the state has decided to reduce its focus on offense type C. (This might be low-level drug-law violators as identified using the BJS_Offense_1 code or any other indicator appearing in the NCRP.) One approach to this problem would be to create the seven offense seriousness categories based on the distribution of median time served and then an category that pertains to offense type C. In fact, this is the strategy we employed when removing drug offenses from the calculation and treating them as their own separate offense serious class. To incorporate such a change, the program would have to loop through an additional offense seriousness category, but this is a minor programming change. The multiplier described in the previous paragraph would now apply to this unique offense type.

[17] In many prison systems, admissions are trending. The estimation takes trends into account using pre-2015 data, so past trends should not be factored into the analysis. However, post-2015, the state may have implemented reforms expected to increase or decrease flows for some of the partitions identified for this study. The projection methodology cannot anticipate those reforms, so they must be built into the methodology.

Simulations

The methodology is intended to make best estimates based on recent trends and historical practices. As discussed above, the program allows the user to introduce external information in the form of a multiplier that increases or decreases the transition probabilities or that increases or decreases the future admission flow. The multipliers apply to the offense types and these are defined by interactions between offense seriousness and criminal history.

External information is likely to take a different form, say, by applying to an offense type rather than an offense seriousness level. For example, suppose the state plans to eliminate prison for all offenders convicted of driving under the influence. There are two ways to proceed. One is to simply delete all DUI offenses from the NCRP data. The 2010 and 2015 stocks would be incorrect because they would exclude DUI but the 2020 stocks would be defensible estimates. The 2020 stock could be compared with 2010 and 2015 stocks built from the entire NCRP data.

An alternative approach would be to treat DUI as a separate seriousness category. The model would project the 2020 stock for the eight seriousness categories and for the ninth special category "DUI". The user could then delete the DUI category from the 2020 stock, or the user could assign the slow multiplier of zero to the DUI category so that the category will have no members in the 2020 stock.

As written, the program assumes eight offense seriousness categories. It is little trouble to add an additional category by (1) defining the category so that it is distinct from the seven offense seriousness categories, (2) changing the number of loops from 8 to 9, and (3) expanding the storage matrix to have 9 rather than 8 rows. The program writes the storage matrices in its output, and this requires no change. However, the program also writes its output to a spreadsheet that is specifically formatted to accept storage matrices with seven rows. The spreadsheet would require redesign.

Discussion

The projections come from a program written in Stata, a statistical computing software package. At a minimum, the program requires NCRP term records for 2010 through 2015 to make 2020 projections. In fact, to construct the criminal history scores, the program requires term records from 2003 through 2015. If the observation window begins after 2003 but before 2011, the criminal history variable is abbreviated – say to a release within six years of the current admissions instead of within seven years. The method would work with a different definition of criminal history. Having a minimum of 2011 through 2015 term records seems essential for a five-year projection.

Not all states meet this minimum criterion. Suppose a state only has term records from 2012 through 2015. Then the methodology could be adapted to make a four-year projection. The program would require some modification to provide four-year projections, and modifications made not be worthwhile given that the NCRP is ongoing so that contributing states are adding additional years of data.

A couple states report stocks but not flows. The vector autoregression could be used with stocks alone. The rest of the modeling would be unnecessary, but working with stocks alone misses the richness of the full model. Specifically, stocks change slower than flows. If flows are going through recent changes, a stock-based model could miss those changes and provide a less rigorous estimate of the 2020 stock.

There are no prison term records for some states. For those states, projections might better be performed using the annual National Prisoner Statistics (NPS) data. Projections would use the vector autoregression procedure, but the rest of the program would be irrelevant. The NPS has the advantage that stocks and flows can appear in the vector autoregression model, but it has the disadvantage that the NPS supports only limited partitioning of the data. When available, the NPS is likely to provide more accurate projections, but of course this cannot be demonstrated.